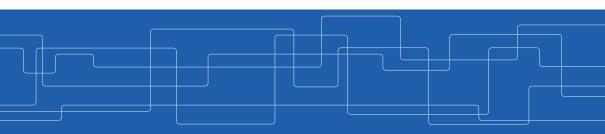


Introduction to Data Stream Processing

Amir H. Payberah payberah@kth.se 19/09/2019



https://id2221kth.github.io



Where Are We?





Stream Processing (1/4)

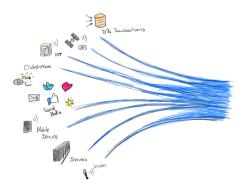
► Stream processing is the act of continuously incorporating new data to compute a result.





Stream Processing (2/4)

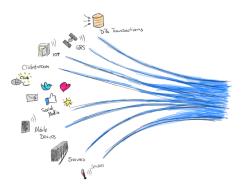
- ► The input data is unbounded.
 - A series of events, no predetermined beginning or end.





Stream Processing (2/4)

- ► The input data is unbounded.
 - A series of events, no predetermined beginning or end.
 - E.g., credit card transactions, clicks on a website, or sensor readings from IoT devices.



Stream Processing (3/4)

▶ User applications can then compute various queries over this stream of events.





Stream Processing (3/4)

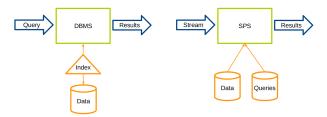
- ▶ User applications can then compute various queries over this stream of events.
 - E.g., tracking a running count of each type of event, or aggregating them into hourly windows.





Stream Processing (4/4)

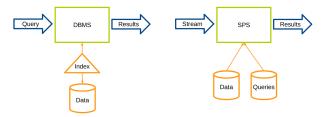
- ▶ Database Management Systems (DBMS): data-at-rest analytics
 - Store and index data before processing it.
 - Process data only when explicitly asked by the users.





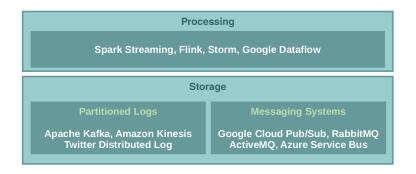
Stream Processing (4/4)

- ► Database Management Systems (DBMS): data-at-rest analytics
 - Store and index data before processing it.
 - Process data only when explicitly asked by the users.
- ► Stream Processing Systems (SPS): data-in-motion analytics
 - Processing information as it flows, without storing them persistently.





Stream Processing Systems Stack

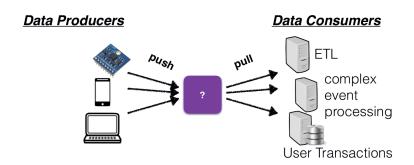




Data Stream Storage

The Problem

▶ We need disseminate streams of events from various producers to various consumers.



Example

► Suppose you have a website, and every time someone loads a page, you send a viewed page event to consumers.

KTH Example

- Suppose you have a website, and every time someone loads a page, you send a viewed page event to consumers.
- ▶ The consumers may do any of the following:
 - Store the message in HDFS for future analysis
 - · Count page views and update a dashboard
 - Trigger an alert if a page view fails
 - Send an email notification to another user



Possible Solution?

► Messaging systems



Message

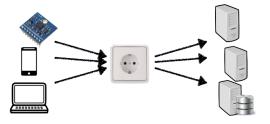
www.defit.org

▶ Messaging system is an approach to notify consumers about new events.

- ▶ Messaging system is an approach to notify consumers about new events.
- Messaging systems
 - Direct messaging
 - Message brokers

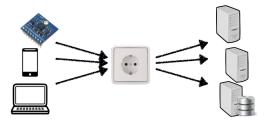


- ▶ Necessary in latency critical applications (e.g., remote surgery).
- ▶ A producer sends a message containing the event, which is pushed to consumers.



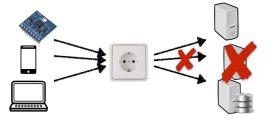


- ▶ Necessary in latency critical applications (e.g., remote surgery).
- ▶ A producer sends a message containing the event, which is pushed to consumers.
- ▶ Both consumers and producers have to be online at the same time.



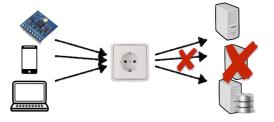


▶ What happens if a consumer crashes or temporarily goes offline? (not durable)



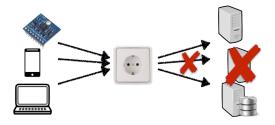


- ▶ What happens if a consumer crashes or temporarily goes offline? (not durable)
- ▶ What happens if producers send messages faster than the consumers can process?



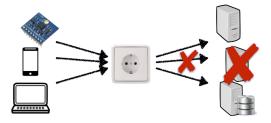


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 - Dropping messages
 - Backpressure





- What happens if a consumer crashes or temporarily goes offline? (not durable)
- What happens if producers send messages faster than the consumers can process?
 - Dropping messages
 - Backpressure
- ▶ We need message brokers that can log events to process at a later time.





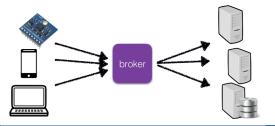


[https://bluesyemre.com/2018/10/16/thousands-of-scientists-publish-a-paper-every-five-days]



Message Broker

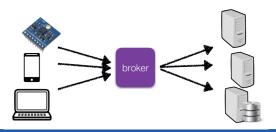
- ► A message broker decouples the producer-consumer interaction.
- ▶ It runs as a server, with producers and consumers connecting to it as clients.





Message Broker

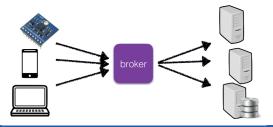
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Message Broker

- ► A message broker decouples the producer-consumer interaction.
- ▶ It runs as a server, with producers and consumers connecting to it as clients.
- ► Producers write messages to the broker, and consumers receive them by reading them from the broker.
- ► Consumers are generally asynchronous.





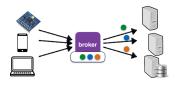
Message Broker (2/2)

▶ When multiple consumers read messages in the same topic.



Message Broker (2/2)

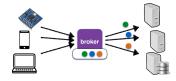
- ▶ When multiple consumers read messages in the same topic.
- ▶ Load balancing: each message is delivered to one of the consumers.



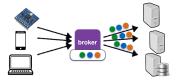


Message Broker (2/2)

- ▶ When multiple consumers read messages in the same topic.
- ▶ Load balancing: each message is delivered to one of the consumers.



► Fan-out: each message is delivered to all of the consumers.





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- ► Log-based message brokers durably store all events in a sequential log.



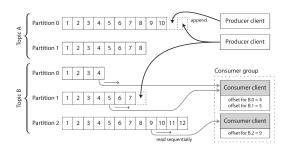
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- ► Log-based message brokers durably store all events in a sequential log.
- ► A log is an append-only sequence of records on disk.
- ▶ A producer sends a message by appending it to the end of the log.
- ► A consumer receives messages by reading the log sequentially.

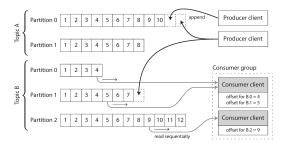


▶ To scale up the system, logs can be partitioned hosted on different machines.



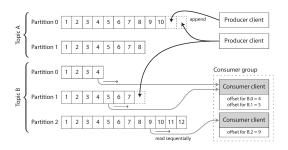


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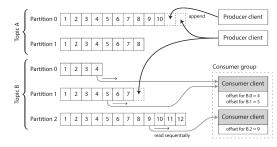
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 Within each partition, the broker assigns a monotonically increasing sequence number (offset) to every message

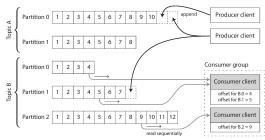




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► No ordering guarantee across partitions.



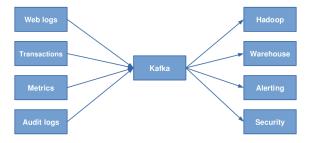


Kafka - A Log-Based Message Broker



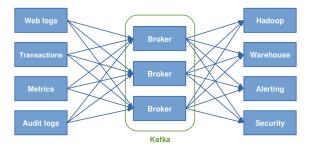


▶ Kafka is a distributed, topic oriented, partitioned, replicated commit log service.



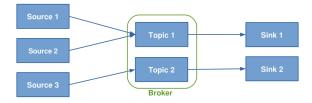


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KTH Kafka (3/5)

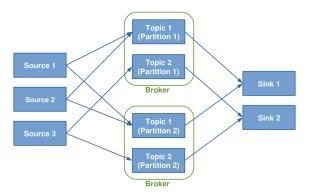
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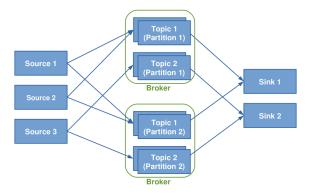


Kafka (4/5)

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Logs, Topics and Partition (1/5)

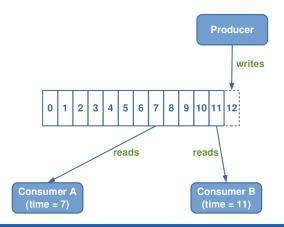
- Kafka is about logs.
- ► Topics are queues: a stream of messages of a particular type

```
jkreps-mn:~ jkreps$ tail -f -n 20 /var/log/apache2/access_log
::1 - - [23/Mar/2014:15:07:00 -0700] "GET /images/apache feather.gif HTTP/1.1" 200 4128
::1 - - [23/Mar/2014:15:07:04 -0700] "GET /images/producer consumer.png HTTP/1.1" 200 86
::1 - - [23/Mar/2014:15:07:04 -0700] "GET /images/log_anatomy.png HTTP/1.1" 200 19579
::1 - [23/Mar/2014:15:07:04 -0700] "GET /images/consumer-groups.ong HTTP/1.1" 200 2682
::1 - - [23/Mar/2014:15:07:04 -0700] "GET /images/log_compaction.png HTTP/1.1" 200 41412
::1 - - [23/Mar/2014:15:07:04 -0700] "GET /documentation.html HTTP/1.1" 200 189893
::1 - - [23/Mar/2014:15:07:04 -0700] "GET /images/log cleaner anatomy.png HTTP/1.1" 200
::1 - - [23/Mar/2014:15:07:04 -0700] "GET /images/kafka log.ong HTTP/1.1" 200 134321
::1 - - [23/Mar/2014:15:07:04 -0700] "GET /images/mirror-maker.png HTTP/1.1" 200 17054
::1 - - [23/Mar/2014:15:08:07 -0700] "GET /documentation.html HTTP/1.1" 200 189937
::1 - - [23/Mar/2014:15:08:07 -0700] "GET /styles.css HTTP/1.1" 304 -
::1 - - [23/Mar/2014:15:08:07 -0700] "GET /images/kafka_logo.png HTTP/1.1" 304 -
::1 - - [23/Mar/2014:15:08:07 -0700] "GET /images/producer consumer.png HTTP/1.1" 304 -
::1 - - [23/Mar/2014:15:08:07 -0700] "GET /images/log anatomy.png HTTP/1.1" 304 -
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::1 - - [23/Mar/2014:15:09:55 -0700] "GET /documentation.html HTTP/1.1" 200 195264
```



Logs, Topics and Partition (2/5)

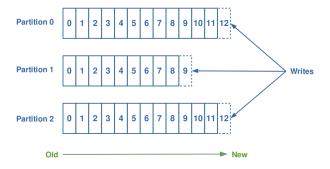
► Each message is assigned a sequential id called an offset.





Logs, Topics and Partition (3/5)

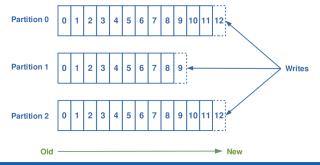
- ► Topics are logical collections of partitions (the physical files).
 - Ordered
 - · Append only
 - Immutable





Logs, Topics and Partition (4/5)

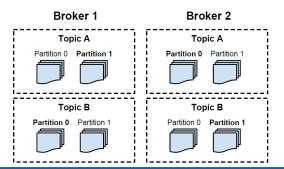
- Ordering is only guaranteed within a partition for a topic.
- Messages sent by a producer to a particular topic partition will be appended in the order they are sent.
- ▶ A consumer instance sees messages in the order they are stored in the log.





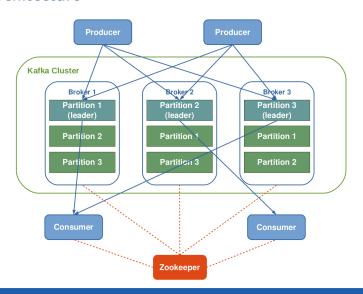
Logs, Topics and Partition (5/5)

- ▶ Partitions of a topic are replicated: fault-tolerance
- ► A broker contains some of the partitions for a topic.
- ▶ One broker is the leader of a partition: all writes and reads must go to the leader.





Kafka Architecture



Coordination

► Kafka uses Zookeeper for the following tasks:



Coordination

- ► Kafka uses Zookeeper for the following tasks:
- ▶ Detecting the addition and the removal of brokers and consumers.
- ▶ Keeping track of the consumed offset of each partition.



State in Kafka

▶ Brokers are sateless: no metadata for consumers-producers in brokers.

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- ▶ Brokers are sateless: no metadata for consumers-producers in brokers.
- ► Consumers are responsible for keeping track of offsets.
- ▶ Messages in queues expire based on pre-configured time periods (e.g., once a day).

Delivery Guarantees

► Kafka guarantees that messages from a single partition are delivered to a consumer in order.

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- ► Kafka only guarantees at-least-once delivery.

 ${\it\# Start the ZooKeeper} \\ {\it zookeeper-server-start.sh config/zookeeper.properties}$

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Start the Kafka server
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```

```
# Start the Kafka server
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```

```
# Create a topic, called "avg"
kafka-topics.sh --create --zookeeper localhost:2181 --replication-factor 1 --partitions 1
--topic avg
```

```
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zookeeper-server-start.sh config/zookeeper.properties
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# Start the Kafka server
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# Produce messages and send them to the topic "avg"
kafka-console-producer.sh --broker-list localhost:9092 --topic avg
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```

```
\# Consume the messages sent to the topic "avg" kafka-console-consumer.sh --bootstrap-server localhost:9092 --topic avg --from-beginning
```



Data Stream Processing

- ▶ Data stream is unbound data, which is broken into a sequence of individual tuples.
- ► A data tuple is the atomic data item in a data stream.
- ► Can be structured, semi-structured, and unstructured.



Streaming Data Processing Design Points

- ► Continuous vs. micro-batch processing
- ► Record-at-a-Time vs. declarative APIs
- ► Event time vs. processing time
- Windowing



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Streaming Data Processing Patterns

- ► Micro-batch systems
 - Batch engines
 - Slicing up the unbounded data into a sets of bounded data, then process each batch.





Streaming Data Processing Patterns

- Micro-batch systems
 - Batch engines
 - Slicing up the unbounded data into a sets of bounded data, then process each batch.



- Continuous processing-based systems
 - Each node in the system continually listens to messages from other nodes and outputs new updates to its child nodes.





Streaming Data Processing Design Points

- ► Continuous vs. micro-batch processing
- ► Record-at-a-Time vs. declarative APIs
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Record-at-a-Time vs. Declarative APIs

- ► Record-at-a-Time API (e.g., Storm)
 - Low-level API
 - Passes each event to the application and let it react.
 - Useful when applications need full control over the processing of data.
 - Complicated factors, such as maintaining state, are governed by the application.



Record-at-a-Time vs. Declarative APIs

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 - Low-level API
 - Passes each event to the application and let it react.
 - Useful when applications need full control over the processing of data.
 - Complicated factors, such as maintaining state, are governed by the application.
- ► Declarative API (e.g., Spark streaming, Flink, Google Dataflow)
 - Aapplications specify what to compute not how to compute it in response to each new event.



Streaming Data Processing Design Points

- ► Continuous vs. micro-batch processing
- ► Record-at-a-Time vs. declarative APIs
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Event Time vs. Processing Time (1/2)

- ▶ Event time: the time at which events actually occurred.
 - Timestamps inserted into each record at the source.
- ▶ Prcosseing time: the time when the record is received at the streaming application.



Event Time vs. Processing Time (2/2)

- ▶ Ideally, event time and processing time should be equal.
- Skew between event time and processing time.



[https://www.oreilly.com/ideas/the-world-beyond-batch-streaming-101]



Streaming Data Processing Design Points

- ► Continuous vs. micro-batch processing
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- Windowing

- ▶ Window: a buffer associated with an input port to retain previously received tuples.
- ► Four different windowing management policies.

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- ► Four different windowing management policies.
 - Count-based policy: the maximum number of tuples a window buffer can hold
 - Delta-based policy: a delta threshold in a tuple attribute
 - Punctuation-based policy: a punctuation is received
 - Time-based policy: based on processing or event time period

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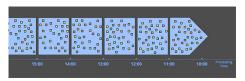
- ▶ Sliding window: supports incremental operations.
 - When the buffer fills up, older tuples are evicted.





Windowing by Processing Time

- ► The system buffers up incoming data into windows until some amount of processing time has passed.
- ► E.g., five-minute fixed windows

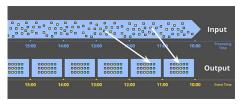


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Windowing by Event Time

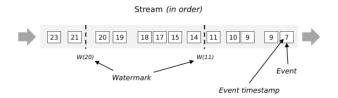
- ▶ Reflect the times at which events actually happened.
- ► Handling out-of-order evnets.



[https://www.oreilly.com/ideas/the-world-beyond-batch-streaming-101]

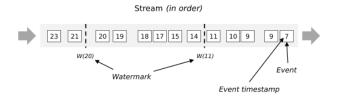


▶ Watermarking helps a stream processing system to deal with lateness.



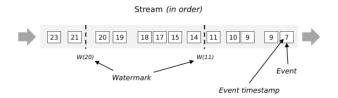


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- ▶ Watermarks flow as part of the data stream and carry a timestamp t.



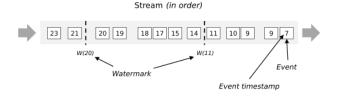


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- ▶ Watermarks flow as part of the data stream and carry a timestamp t.
- ▶ A watermark is a threshold to specify how long the system waits for late events.



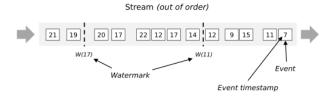


- ▶ Watermarking helps a stream processing system to deal with lateness.
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- ▶ A watermark is a threshold to specify how long the system waits for late events.
- ► Streaming systems uses watermarks to measure progress in event time.



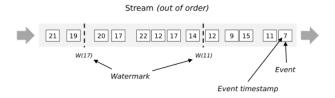


- ► A W(t) declares that event time has reached time t in that stream
 - There should be no more elements from the stream with a timestamp $t' \leq t$.



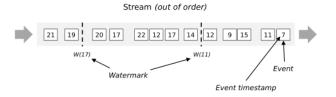


- ► A W(t) declares that event time has reached time t in that stream
 - There should be no more elements from the stream with a timestamp $t' \leq t$.
- ▶ It is possible that certain elements will violate the watermark condition.
 - After the W(t) has occurred, more elements with timestamp $t' \le t$ will occur.



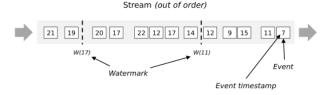


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- ▶ If an arriving event lies within the watermark, it gets used to update a query.
- ► Streaming programs may explicitly expect some late elements.



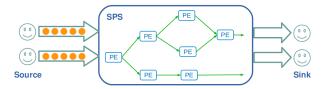


Streaming Data Processing Model



Streaming Data Processing

- ▶ The tuples are processed by the application's operators or processing element (PE).
- ► A PE is the basic functional unit in an application.
 - A PE processes input tuples, applies a function, and outputs tuples.
 - A set of PEs and stream connections, organized into a data flow graph.



- ▶ A PE can either maintain internal state across tuples while processing them, or process tuples independently of each other.
- ► Stateful vs. stateless tasks

PEs States (2/3)

► Stateless tasks: do not maintain state and process each tuple independently of prior history, or even from the order of arrival of tuples.

PEs States (2/3)

- ► Stateless tasks: do not maintain state and process each tuple independently of prior history, or even from the order of arrival of tuples.
- Easily parallelized.
- ► No synchronization.
- ► Restart upon failures without the need of any recovery procedure.

PEs States (3/3)

► Stateful tasks: involves maintaining information across different tuples to detect complex patterns.

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- ► A PE is usually a synopsis of the tuples received so far.
- ► A subset of recent tuples kept in a window buffer.



Runtime Systems



Job and Job Management

- ▶ At runtime, an application is represented by one or more jobs.
- ▶ Jobs are deployed as a collection of PEs.
- ▶ Job management component must identify and track individual PEs, the jobs they belong to, and associate them with the user that instantiated them.



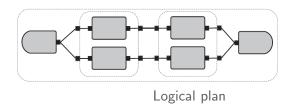
Logical Plan vs. Physical Plan (1/3)

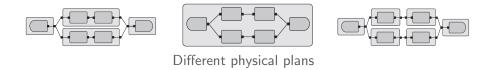
- ► Logical plan: a data flow graph, where the vertices correspond to PEs, and the edges to stream connections.
- ▶ Physical plan: a data flow graph, where the vertices correspond to OS processes, and the edges to transport connections.





Logical Plan vs. Physical Plan (2/3)







Logical Plan vs. Physical Plan (3/3)

- ▶ How to map a network of PEs onto the physical network of nodes?
 - Parallelization
 - Fault tolerance
 - Optimization

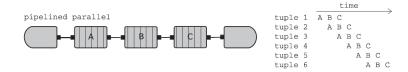


Parallelization

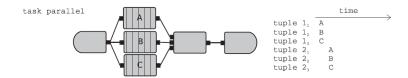
Parallelization

- ▶ How to scale with increasing the number queries and the rate of incoming events?
- ► Three forms of parallelisms.
 - Pipelined parallelism
 - Task parallelism
 - Data parallelism

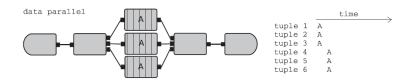
► Sequential stages of a computation execute concurrently for different data items.



▶ Independent processing stages of a larger computation are executed concurrently on the same or distinct data items.



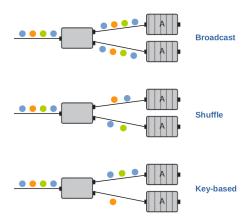
▶ The same computation takes place concurrently on different data items.





Data Parallelism (2/2)

▶ How to allocate data items to each computation instance?





Fault Tolerance

- ▶ The recovery methods of streaming frameworks must take:
 - Correctness, e.g., data loss and duplicates
 - Performance, e.g., low latency

Delivery Guarantees

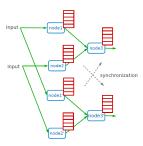
- ► At-least-once: might appear many times
- ► Exactly-once: is consumed just once

- ► Active backup
- ► Passive backup
- ► Upstream backup



Recovery Methods - Active Backup

- ► Each processing node has an associated backup node.
- ▶ Both primary and backup nodes are given the same input.

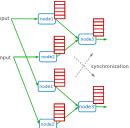




Recovery Methods - Active Backup

- ► Each processing node has an associated backup node.
- ▶ Both primary and backup nodes are given the same input.

▶ If the primary fails, the backup takes over by sending the logged tuples to all down-stream neighbors and then continuing its processing.





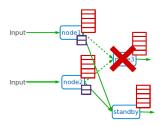
Recovery Methods - Passive Backup

- ▶ Periodically check-points processing state to a shared storage.
- ▶ The backup node takes over from the latest checkpoint when the primary fails.



Recovery Methods - Upstream Backup

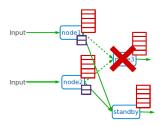
▶ Upstream nodes store the tuples until the downstream nodes acknowledge them.





Recovery Methods - Upstream Backup

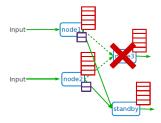
- ▶ Upstream nodes store the tuples until the downstream nodes acknowledge them.
- ▶ If a node fails, an empty node rebuilds the latest state of the failed primary from the logs kept at the upstream server.





Recovery Methods - Upstream Backup

- ▶ Upstream nodes store the tuples until the downstream nodes acknowledge them.
- ▶ If a node fails, an empty node rebuilds the latest state of the failed primary from the logs kept at the upstream server.
- ► There is no backup node in this model.





Optimization



Optimization - Early Data Reduction

- ► Reducing the data volume as early as possible.
 - Sampling, filtering, quantization, projection, and aggregation.



Optimization - Reordering

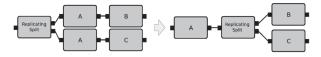
- ► Operator reordering
 - Executing the computationally cheaper operator and/or the more selective operator earlier reduces the overall cost.





Optimization - Redundancy Elimination

▶ Removing the redundant segments from a data flow graph.





Optimization - Operator Fusion

- ▶ It changes only the physical layout.
- ► If two operators of the two ends of a stream connection are placed on different hosts: non-negligible network cost



Optimization - Operator Fusion

- It changes only the physical layout.
- ► If two operators of the two ends of a stream connection are placed on different hosts: non-negligible network cost
- ▶ It is effective, if the per-tuple processing cost of the operators being fused is lower than the cost of transferring tuples across the stream connection.



Optimization - Tuple Batching

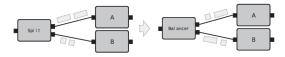
- ▶ Processing a group of tuples in every iteration of an operator's internal algorithm.
- ► Can increase the throughput at the expense of higher latency.





Optimization - Load Balancing

- ► Flow partitioning to distribute the workload, e.g., data or task parallelism.
- ▶ Distributing the load evenly across the different subflows.





Optimization - Load Shedding

- ▶ Used by an operator to reduce the amount of computational resources it uses.
 - Decrease the operator latency, and improve the throughput.
- ▶ Different techniques: dropping incoming tuples, data reduction techniques (e.g., sampling), ...





Summary

Summary

- Messaging system and partitioned logs
- Decoupling producers and consumers
- ► Kafka: distributed, topic oriented, partitioned, replicated log service
- ► Logs, topcs, partition
- ► Kafka architecture: producer, consumer, broker, coordinator

Summary

- ► SPS vs. DBMS
- ▶ Data stream, unbounded data, tuples
- ► Event-time vs. processing time
- ► Micro-batch vs. continues processing (windowing)
- ▶ PEs and dataflow
- Stateless vs. Stateful PEs
- ▶ SPS runtime: parallelization, fault-tolerance, optimization

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Questions?